# How the quasispecies evolution depends on the topology of the genome space

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#### Abstract

We compared the properties of the error threshold transition in quasispecies evolution for three different topologies of the genome space. They are a) hypercube b) rugged landscape modelled by an ultrametric space, and c) holey landscape modelled by Bethe lattice. In all studied topologies the phase transition exists. We calculated the critical exponents in all the cases. For the critical exponent corresponding to appropriately defined susceptibility we found super-universal value.

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#### 1 Introduction

The conceptual simplicity and readiness for mathematical description, along with obvious practical relevance makes the Darwinian evolution a prominent subject of theoretical biology. Moreover, the formalisation in terms of stochastic processes reveals close relations to many problems studied before in theoretical physics. Therefore, it is natural to look for physical tools which may answer biologists' questions about natural evolution. A lot of effort was devoted to this area recently [1–9].

The process of the biological evolution consists in three steps, though two of them are simultaneous:  $reproduction \rightarrow mutation \rightarrow selection$ . The impor-

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tant thing to note is that the *biological fitness* function which denotes individuals' ability to produce viable offspring is dependent on their phenotype. On the other hand, the mutations occur in the genotype — information stored in a sequence of DNA. The overwhelming complexity of the fitness function, which assigns to each microscopic genotype corresponding macroscopic phenotype, makes the theoretical treatment of evolution an extremely complicated task.

Simplifications of the problem are necessary. One of the most prominent schemes was developed within the *quasispecies* model of the biological evolution, introduced by Eigen [10]. It showed to be plausible and very useful when investigating the mechanisms of microevolution. In the language of physics we can roughly speak of diffusion in a complicated potential. Originally it was introduced as a model of chemical prebiotic evolution, but it is also reasonable to use it for viruses and bacteria which do not haven too complex genome. Among the host of other approaches, let us mention at least the model of coevolution described by Kauffman's NKCS model [11,12].

Very clear and visual presentation of the evolutionary process is to consider it as a random walk in the *fitness landscape*. This is a surface above the genome space, where the altitude of each point is determined by the fitness attributed to the corresponding genotype. In fact, the fitness landscape is not static, as it strongly depends on the ever changing environment, which includes interactions with (co)evolving species as well as abiotic influences [13]. The movement in the fitness landscape is driven by the mutations and optimal genotypes are situated on tops of peaks in the landscape.

A broad set of different fitness landscapes was used recently to study the behaviour of the evolutionary system. These models included both static [14,15] and dynamic landscapes [13,16–18]. They include the *sharply-peaked landscape* (SPL), the *Fujiyama landscape* or the *holey landscape* (HL). Several recent reviews summarise various approaches explored [13,19–21].

In the Eigen's quasispecies model an individual is characterised by a sequence of d nucleotides (or loci)  $\mathbf{s} = \{s_1, s_2, s_3, \dots, s_d\}$ . In real situation we should consider that there are 4 main nucleotides A, G, C, T(U), so the alphabet contains four letters. Two of them are pyrimidines and the other two are purines. To make the treatment mathematically simpler, we will use only two-letter alphabet  $\{0,1\}$ . We may interpret this simplification in two alternative ways. We can consider putting the digit 0 in the site of the sequence when in the same position in the nucleotide acid is a pyrimidine and 1 if there is a purine. Or, we can consider a set of loci and for each locus suggest exactly two possible alleles, denoted by 0 and 1.

In every position of the sequence a mutation can occur with a probability  $\mu$ . In our work we consider only point mutations (transversions and transitions

or an exchange of alleles in a certain locus) which are only a part of all processes which change genotype and consequently the phenotype. For example we neglect duplications which, it seems, are important for our understanding of protein interaction networks, see [22–24]. The mutation is then an exchange of 1 and 0 in a particular site in the sequence or in a certain locus. The on site mutation rate  $\mu$  is considered to be uniform for all sites of the sequence, although this is not the case which we see in fact. It is considered that this simplification does not change the results of the model.

The properties of the evolutionary process, which we are going to compare in the article, are the critical coefficients of the error threshold transition. The error threshold is the phase transition found in SPL which separates two regimes of the quasispecies evolution — the adaptive regime and wandering regime. In the adaptive regime the cloud of quasispecies is formed around the wildtype, whereas in the wandering regime no wildtype is formed due to a mutation load.

The error threshold phenomenon comes out of the competition between the selective advantage of the wildtype  $\alpha$  and the mutation load presented by the rate  $\mu$  and the genome length d. The threshold is characterised by the specific value of the selective advantage  $\alpha_c$ . From the physical point of view, the error threshold may be thought of as a dynamic phase transition from localised to extended ground-state eigenvector. Recently it was shown [25] that coevolution of several species may drive the system close to the error threshold. It is therefore highly biologically relevant to study the properties of the error threshold transition in detail.

It is evident that the native geometry of the genome space is the hypercube  $S = \{0, 1\}^d$ . So, this is the natural starting point when building a model for a fitness landscape. The main focus will be aimed at the presence or absence of adaptive regime induced by a single maximum in the fitness landscape. Therefore, the first thing to try is the sharply–peaked landscape on the hypercube. This model was solved exactly by Galluccio et al. [26,27].

However, the real landscapes are far more complicated. Indeed, it is expected that rugged landscapes with many competing maxima represent a realistic picture [1]. Fortunately enough, such landscapes are well–known in the theory of spin glasses [28] and a "spin–glass" theory of evolution was investigated [29].

The main result coming from the spin–glass theory is the *ultrametric structure* of the minima in the free–energy landscape of spin glasses, which can be translated into ultrametric or hierarchical structure of maxima in the corresponding fitness landscape.

Somewhat more coarse–grained description of the evolution may arise, if we

assume the ultrametric structure of fitness maxima. Indeed, we may think of the evolution as a hopping process between various peaks, where the system spends most of its time, while the detailed course of the hops, composed of many individual point mutations, can be accounted for phenomenologically by tuning appropriately the hopping probabilities.

Here, we will be interested again in the error—threshold transition, now interpreted in such a way that all but one of the peaks have the same weight, while the singled—out peak is higher and corresponds to the "wildtype" of the sharply—peaked landscape. Therefore, the treatment can be very similar to SPL from the mathematical point of view, but differs significantly in that now we take into account, at least approximately, the ruggedness of the real fitness landscape.

Yet another approach to the modelling of the fitness landscape is possible, namely considering the holey landscape. Indeed, most of the point mutations which may occur at the basic level of the evolutionary picture are lethal for the individual. Therefore, the hypercube does not represent a good approximation to the evolutionary dynamics, because only few of the hypercube's edges represent paths to possible new genomes. A sparsely connected set of points selected at some of the hypercube corners is perhaps better choice.

The problem resembles the study of topologically disordered solids, where the random network of bonds is often well modelled by the Bethe lattice. Therefore, third geometry we investigate in our work is that of the Bethe lattice. Again, as in the previous cases, one of the points will be considered as the "wildtype" with larger fitness, while all other points will have uniform fitness (smaller than the wildtype).

#### 2 General scheme for sharply–peaked and related landscapes

In the quasispecies model, evolution of the size  $p_i$  of an asexual population for the genome represented by the lattice site i is governed by the equation

$$\dot{p}_i(t) = \sum_j T_{ij} p_j(t) \quad . \tag{1}$$

describing a Markov process in the genome space.

The quantity  $p_i$  will represent the relative population size, or it will be proportional to the probability of a certain individual to belong to the population in the site i. In so doing, we tacitly assume to work within the *infinite population* limit.

The time evolution may take place in discrete time; in this case the derivative corresponds to  $\dot{p}(t) \equiv p(t+1) - p(t)$ . However, in our work the continuous–time description will be used,  $\dot{p}(t) \equiv \frac{\partial p(t)}{\partial t}$ , unless explicitly stated the opposite.

The dynamical matrix can be written in the form  $T_{ij} = Q_{ij} + \delta_{ij}(A_i - D)$ , where  $A_j$  is proportional to the fitness of the genome i and so it represents a reproductive potential of the quasispecies. The mutation matrix  $Q_{ij}$  represents the rate of mutation from the point i in the genome space to another point j. The diagonal elements of the matrix  $Q_{ii}$  are the probability rates of the perfect replication of the individual i. We may also introduce the homogeneous external stress which conserves the population size, through the decay rate D.

The dynamical matrix  $T_{ij}$  is supposed to be symmetric. This allows us to apply the common machinery of Green functions. Indeed, the main object of interest will be the resolvent (Green function) of the dynamical matrix

$$\mathcal{G}(\zeta) = \frac{1}{\zeta - T} \tag{2}$$

This formalism is particularly suitable for the case of the sharply–peaked landscape. Indeed, we suppose that the dynamical matrix can be decomposed as  $T = T^0 + V$ , where  $T^0$  corresponds to the flat landscape of neutral evolution and the perturbation V describes the presence of the peak localised at point i = 1,

$$V_{ij} = \alpha \delta_{ij} \delta_{i1} \tag{3}$$

Indeed, supposing that we are able to fully solve the neutral evolution, i. e. to find the "free" resolvent  $\mathcal{G}^0 = (\zeta - T^0)^{-1}$ , the error threshold is closely related to the existence of the split-off pole in the resolvent  $\mathcal{G}(\zeta)$ . For the position of the pole z we have the equation (Koster–Slater condition)

$$\frac{1}{\alpha} = G(z) \tag{4}$$

where  $G(\zeta) = \mathcal{G}_{11}^0(\zeta)$  is the diagonal matrix element of the free resolvent at the site of the peak. If the equation (4) has a real solution, there is a split-off pole, the stationary state is localised and we are in the adaptive phase of the evolution. On the contrary, the absence of a real solution indicates that the stationary state is extended and we are in the wandering regime.

Our strategy in the following will consist in calculating the free resolvent for various models of the genome space and then analysing the solution of the equation (4). To start with, we reexamine the previously obtained results on the hypercube.

# 3 Exact solution on the hypercube

In the article [26] Galluccio et al. investigated the evolution of the quasispecies in the sharply–peaked landscape on the hypercubic lattice. The model is exactly soluble. Let us start by re-derivation of their main results.

The following assumptions are made in [26]:

- (1) The topology of the genome space is the hypercube.
- (2) The evolution takes place in discrete time, i.e.  $\dot{p} \equiv p(t+1) p(t)$ .
- (3) At one time step, only single point mutation occurring with probability  $\mu$  is allowed. Therefore, the mutation matrix connects only the nearest neighbours along the edges of the hypercube.
- (4) The fitness landscape is flat with only a single point which takes the additive selective advantage  $\alpha > 0$  (sharply–peaked landscape).

The consequence of allowing single point mutations in discrete time evolution, is that they had to restrict a mean number of mutations per genome — genomic mutation rate  $\overline{\mu} = \mu d$  — to be less than 1. This need not to be valid in general, for example in natural viral populations, as is shown in paper [30] where the genomic mutation rates are estimated for measles virus, poliovirus, VSV and rhinovirus. The values are in the range from 0.13 to 1.15 mutations per replication. In other work [31] the genomic mutation rates were estimated in the range from 0.475 to 4.28 mutations per replication. This is the reason why we decided to use a continuous time approximation. The value  $\mu$  can be easily found if we know the length of the life cycle and the mutation rate per site per replication. We took the rate from mentioned articles. The "lifetime" of measles virus or more precisely the time required for production of a new burst of viral particles is in the order of hours or days. So, for example, the mutation rate in RNA virus is around  $\mu = 10^{-4}$  per site per generation [30]. With the considered generation time 20 hours we get approximately  $\mu = 1.5 \times 10^{-9}$ per site per second. The presented models of quasispecies have to respect the values of  $\mu$  and the length of the sequence which is in order of kilobases. For instance, d = 15,894 bases for the measles virus [30]. Therefore, we choose the continuous-time description of the evolution process instead. The rest of the assumptions listed above remain valid. Let us proceed with formalisation of the above assumptions.

The genome space is the d-dimensional hypercube,  $S = \{0, 1\}^d$ . The points in the genome space are the sequences of base pairs  $i = [i_1, i_2, ..., i_d] \in S$ . Let us denote  $\bar{i}(k) \in S$  the sequence which differs from i by the point mutation at k-th base pair,  $(\bar{i}(k))_l = i_l + (1 - 2i_l)\delta_{kl}$ . Then the dynamic matrix of the

neutral evolution corresponds to the diffusion in the hypercube

$$T_{ij}^{0} = \mu \sum_{k=1}^{d} \delta_{j\bar{i}(k)} - \mu \, d \, \delta_{ij} \tag{5}$$

The sharp peak located at the wildtype sequence  $0 \equiv [0, ...0] \in \mathcal{S}$  contributes by the term expressed by Eq. (3).

The general condition (4) assumes very simple form, when we use the Fourier transform in the space S and divide the space with respect to the Hamming distance h from the wildtype. The number of sequences in each Hamming distance class is given by the binomial coefficient  $\binom{d}{h}$ . We obtain

$$\frac{1}{\alpha} = \frac{1}{2^d} \sum_{h=0}^d \binom{d}{h} \frac{1}{z + 2\mu h} \quad . \tag{6}$$

In the limit  $2^d \to \infty$  the calculation further simplifies. The point is that the binomial distribution of classes reduces in that limit to a very thin and high band which we approximate by a  $\delta$ -function in the mean value,  $\binom{d}{h} \sim 2^d \delta(h - d/2)$ .

However, we should be aware that this approximation holds only for z not too close to 0. On the other hand, the error threshold itself is characterised by the fact that the solution z of the equation (6) approaches to 0. Therefore, we have to consider in (6) separately the term with h = 0, while the rest of the sum, for h > 0, is approximated by the  $\delta$ -function as hinted above. Hence, the approximate form of the Eq. (6) is <sup>3</sup>

$$\frac{1}{\alpha} = \frac{1}{2^d} \frac{1}{z} + \frac{2^d - 1}{2^d} \frac{1}{z + \mu d}.$$
 (7)

The approximation we use here goes along different line than the one used in [26] but it gives the same results in lowest order.

The solution z of Eq. (7) is

$$z = \frac{1}{2} \left( \alpha - \mu d + \sqrt{(\alpha - \mu d)^2 + \frac{4\alpha\mu d}{2^d}} \right). \tag{8}$$

<sup>&</sup>lt;sup>3</sup> we have done numerical solutions of (6) and (7) for d=44 and even for such a short sequence the approximative formula fits very well. So, we expect very good agreement for the genomes with the length comparable to e. g. the measles virus's genome.

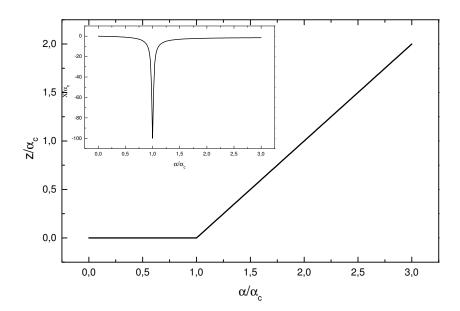


Fig. 1. A graphical view of z and  $\chi$  (inset) for the quasispecies evolution on the hypercubic lattice.

Now we perform the limit  $d \to \infty$ . It requires some care, as the product of  $\mu d$  must stay finite, otherwise diagonal elements of the transfer matrix diverge. So we fix  $\bar{\mu} = \mu d$  constant. Performing the limit we have to distinguish two different cases,

$$z = \frac{1}{2^d} \frac{2\alpha \bar{\mu}}{\bar{\mu} - \alpha} \quad \text{for} \quad (\alpha - \bar{\mu}) < 0$$

$$z = \alpha - \bar{\mu} \quad \text{for} \quad (\alpha - \bar{\mu}) > 0. \tag{9}$$

As we see behaviour of the largest eigenvalue z changes sharply in the point  $\alpha_c = \bar{\mu}$ . Here we recognise the *error threshold*.

Our next aim is to calculate the *susceptibility* of the quasispecies to a change of the sequence length. Elongation of the sequence increases a number of possible sequences  $N=2^d$ . The susceptibility, then, shows us how the largest eigenvalue and thus a relative fitness of the wildtype changes with the "volume" of the sequence space.

We differentiate (8) with the respect to N. Then the limit  $N \to \infty$  is done. Defining

$$\chi = \lim_{N \to \infty} N^2 \frac{\partial z}{\partial N} \tag{10}$$

we get in the vicinity of the error threshold

$$\chi = -\frac{\alpha \alpha_c}{|\alpha - \alpha_c|} \tag{11}$$

Now we introduce critical exponents  $\beta^{\pm}$ ,  $\gamma^{\pm}$ . They characterise behaviour of the largest eigenvalue z and the susceptibility, respectively, close to the error threshold, from the left (-) and right (+) side. In the vicinity of the error threshold we assume the critical behaviour

$$\alpha < \alpha_c \qquad z \sim N^{-1} |\alpha - \alpha_c|^{\beta^-} \qquad \chi \sim |\alpha - \alpha_c|^{\gamma^-} \quad ,$$
  

$$\alpha > \alpha_c \qquad z \sim |\alpha - \alpha_c|^{\beta^+} \qquad \chi \sim |\alpha - \alpha_c|^{\gamma^+} \quad .$$
(12)

From (9) we see that z behaves close to the error threshold as a power function with the exponents  $\beta^- = -1$  and  $\beta^+ = 1$ , and the Eq. (11) implies that  $\gamma^- = \gamma^+ = -1$ .

### 4 The Quasispecies Evolution in an Ultrametric Space

The sharply—peaked landscape is certainly an oversimplified approximation. It describes the adaptation close to a single selected peak within the true fitness landscape. Indeed, in reality the landscape is rugged and consists of very many concurrent peaks. In order to investigate their combined effect, we must turn to some model scheme.

It was realised quite a long ago that complicated free–energy landscapes with many minima are characteristic for disordered spin systems, namely spin glasses [28]. This analogy was brought to biology within the spin–glass model of evolution [29]. The main result of the spin–glass theory, which will be relevant for us here, is the tree–like (or ultrametric) structure of minima in the free–energy landscape [28,32]. We therefore assume that the same ultrametric structure of peaks will be characteristic for the rugged fitness landscape. Then, we will observe the evolution on a "mesoscopic" time–scale, where a single event will be the jump from one peak to the other. Clearly, it consists of many "microscopic" events, i. e. point mutations in the DNA sequence.

The evolution takes place in the space S constructed as the set of endpoints of a regular three with K levels, where at each level every branch splits into p new branches. The ultrametric tree is illustrated in the left panel of Fig. 2.

From the mathematical point of view, the ultrametric structure is described through p-adic numbers and we will use the p-adic Fourier transform as the

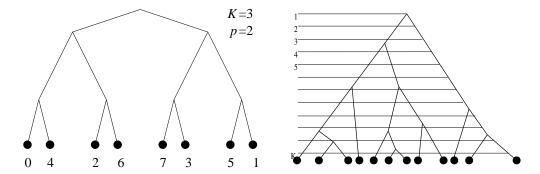


Fig. 2. (Left) The ultrametric tree with three levels and with the branching 2. Below are written 2-adic numbers. (Right) Division of an arbitrary tree in K levels with an imperfect branching  $p \to 1^+$ . The difference p-1 is proportional to the probability of branching in an arbitrary level.

main tool for the solution. The ultrametric space is represented by the set  $S = \{0, 1, 2, ..., p^K - 1\}$  endowed with ultrametric distance between each pair of points, denoted  $|i - j|_p$  for  $i, j \in S$ . We refer the reader to the Appendix for necessary definitions and formulae. The diffusion in the ultrametric space was already thoroughly studied before in the context of spin-glass dynamics [33–38] and the concept of p-adic Fourier transform was developed quite long ago in the mathematic literature [39], and was used implicitly (see e. g. [40]) but its use in physics was made explicit only recently [41–44].

The ultrametric structure will be reflected by the fact that the probability of jumps (mutations) from one point to the other will depend only on the ultrametric distance between the two points. It is analogous to the hypercube, where the mutation probability depends only on the Hamming distance.

Movement of the individual on the ultrametric lattice is driven by the dynamic matrix T which is similar to the one used on the hypercubic lattice. There is one important difference — in the previous case jumps only to the nearest neighbours were considered, but now we must allow a possibility to jump further, otherwise we get evolution only in one isolated branch of the tree.

The evolution in ultrametric analog of the sharply–peaked landscape is described again by the equation (1) where now the "unperturbed" matrix  $T^0$  reflects the symmetry of the ultrametric space. This means that the value of the matrix element  $T^0_{ij}$  depends only on the ultrametric distance between the points i and j. The "perturbation" V corresponds to the single site with selective advantage. We can write explicitly

$$T_{ij}^{0} = \tilde{T}$$
 if  $i = j$   
 $T_{ij}^{0} = T_{m}$  if  $|i - j|_{p} = p^{-m}$  , (13)  
 $V_{ij} = \alpha \, \delta_{ij} \delta_{i0}$  .

Moreover, we will require that the bare transition matrix conserves probability. This fixes the value of the diagonal element,

$$\tilde{T} = -\sum_{b(\neq a)} T_{ab} = -\sum_{m=0}^{K-1} (p-1)p^m T_m$$
(14)

This requirement is not substantial for our treatment, but simplifies somewhat the formulae. Especially it has the consequence that the matrix  $T^0$  has an uniform eigenvector (1, 1, ..., 1) with corresponding eigenvalue equal to 0.

Thus, the fitness landscape is fully described by the sequence of K numbers  $T_0, T_1, ..., T_{K-1}$  and the parameter  $\alpha$ . As  $T_m^0$  is the probability of hopping to the distance  $p^{-m}$ , it is natural to require that

$$T_{m+1}^0 > T_m^0 \tag{15}$$

To follow the general scheme of section 2 we should first find the unperturbed resolvent  $\mathcal{G}^0(\zeta) = (\zeta - T^0)^{-1}$ . So, we need to diagonalise the matrix  $T^0$ .

To this end we use the *p*-adic Fourier transform. For details we refer the reader to the Appendix. The basic result is, that the eigenvalues of the matrix  $T^0$  are  $\hat{T}_m$ , m = 0, 1, ..., K, where

$$\hat{T}_{0} = \tilde{T} + \sum_{l=0}^{K-1} T_{l} p^{K-l-1} (p-1)$$

$$\hat{T}_{m} = \tilde{T} + \sum_{l=m}^{K-1} T_{l} p^{K-l-1} (p-1) - T_{m-1} p^{K-m}, \quad m = 1, \dots, K.$$
(16)

From the conditions (14) and (15) we can immediately deduce that  $\hat{T}_0 = 0$  is the maximum eigenvalue, all other eigenvalues are negative and  $\hat{T}_{m+1}^0 < \hat{T}_m^0$ . Using the inverse p-adic Fourier transform we get for the unperturbed resolvent the expression

$$G(z) = \frac{1}{p^K} \left[ \frac{1}{z} + \sum_{l=1}^K \frac{p^{l-1}(p-1)}{z - \hat{T}_l} \right]$$
 (17)

Introducing the normalised density of states (DOS) as

$$\mathcal{D}(\hat{T}) = \frac{1}{N} (\delta(\hat{T}) + \sum_{j=1}^{K} p^{j-1} (p-1)\delta(\hat{T} - \hat{T}_j))$$
 (18)

we can write the Koster-Slater condition (4) in general form

$$\frac{1}{\alpha} = \int \frac{\mathcal{D}(\hat{T})}{z - \hat{T}} \quad . \tag{19}$$

Clearly, the factor  $p^{j-1}(p-1)$  is the multiplicity of the eigenvalue  $T_i$ .

Let us come back to biological aspects. Each possible quasispecies has got a certain number of alleles, (or sets of subsequences) but we can not consider that every combination of those alleles forms a quasispecies which is able to survive. In fact, the ultrametric tree need not be regular but bears some level of randomness. The ultrametric space considered so far was regular, characterised by fixed branching ration p. We shall take into account the randomness by the following approximate procedure.

Let us take an arbitrary tree, maybe random. With the number of distinct end-points  $N = p^K$  kept fixed we enlarge the number of levels,  $K \to \infty$ . We can freely do so, as the definition of levels is arbitrary: if no branches appear at certain level, we simply have p = 1 locally. With this definition, p may assume different values at different levels as well as at different branches within the same level. The randomness of the tree is then translated into the set of random p-s. We illustrate the situation in the Fig. 2. The approximation consists in characterising the tree by an average value of p, which now may be any real number larger than 1. Furthermore, we will assume that the properties of trees with non-integer values of p can be approximately calculated by analytical continuation from the results obtained for regular, non-random trees and arbitrary integer p. Moreover, we should keep in mind that with p fixed and diverging number of levels p we should make the limit  $p \to 1^+$ . At the end of the calculations, we will make also the thermodynamic limit  $p \to 1^+$ .

Therefore, we take the formulae obtained before for general p and suppose the variable p is now a real number. Then, we will perform the limits

first: 
$$K \to \infty$$
,  $p \to 1^+$  with  $N = p^K$  fixed next:  $N \to \infty$  (20)

Now we should specify the form of the jump rates  $T_m$ . The rate  $T_m$  of a certain individual to mutate to some other with the sequence which is in the ultrametric distance  $p^{-m}$  from the original one will be considered in the form

$$T_m = \mu \, p^{(m-K)\tau} \quad . \tag{21}$$

We solve this case for the value of  $2 > \tau > 1$ . We will see later that this is indeed the interval relevant for the error-threshold phenomenon.

The choice of an arbitrary power  $\tau$  allows simulation of a quite general situation. In the limit  $p \to 1$  possible mutation rates to distinct sites are in a very wide range, starting in the value  $\mu p^{-(K-1)\tau}$  and ending with the highest possible jump rate  $\mu$ . And this is exactly, in our opinion, what we find in reality — a probability rate of the jump from one codon sequence (or a certain set of alleles) to other is not uniform.

In order to solve the equation (19) we need to compute the density of states (18). The eigenvalues of T can be easily found using the Fourier transform. A value of the diagonal element  $\tilde{T}$  is again established with the help of the condition that the sum of elements of the matrix's column equals zero, i. e.  $\hat{T}_0 = 0$ .

$$\hat{T}_m = -\frac{\mu}{p} \frac{p-1}{p^{\tau-1}-1} p^{-(\tau-1)K} \left( p^{(\tau-1)M} \left( 1 + \frac{p^{\tau-1}-1}{p^{\tau-1}(p-1)} \right) - 1 \right)$$
 (22)

The density of states  $\mathcal{D}(\hat{T})$  will be calculated in the limit (20). Its support can be found easily by computing the lowest eigenvalue  $\hat{T}_K$ , which in the limit (20) is equal to  $\hat{T}_{\infty} = -\frac{\mu\tau}{\tau-1}$ . Substituting  $x = p^m$  into (22) and inverting the dependence we obtain the function  $x(\hat{T})$ , hence

$$\mathcal{D}(\hat{T}) = \frac{1}{N} \left| \frac{\mathrm{d}x}{\mathrm{d}\hat{T}} \right| = \frac{1}{\tau - 1} \left( \frac{\tau - 1}{\mu \tau} \right)^{\frac{1}{\tau - 1}} \left( -\hat{T} \right)^{\frac{2 - \tau}{\tau - 1}} \tag{23}$$

for  $\hat{T} \in (-\frac{\mu\tau}{\tau-1}, 0)$  and  $\mathcal{D}(\hat{T}) = 0$  outside this interval.

The equation for the split-off eigenvalue z now becomes

$$\frac{(\tau - 1)\bar{\mu}^{\frac{1}{\tau - 1}}}{\alpha} = \int_0^{\bar{\mu}} \frac{y^{\varepsilon}}{z + y} dy \tag{24}$$

where we denoted

$$\varepsilon = \frac{2 - \tau}{\tau - 1} \quad . \tag{25}$$

and

$$\bar{\mu} = \frac{\mu \, \tau}{\tau - 1} \tag{26}$$

The integral on the RHS of (24) is, for non-integer  $\varepsilon$ ,

$$\int_0^{\bar{\mu}} \frac{y^{\varepsilon}}{z+y} dy = \frac{1}{\varepsilon} \bar{\mu}^{\varepsilon} - \frac{\pi}{\sin \varepsilon \pi} z^{\varepsilon} + z \bar{\mu}^{\varepsilon-1} \sum_{k=0}^{\infty} \frac{1}{k+1-\varepsilon} \left(-\frac{z}{\bar{\mu}}\right)^k \quad . \tag{27}$$

(For integer values of  $\varepsilon$  the infinite series becomes a finite sum accompanied by a logarithmic correction). When analysing the equation (24) we must distinguish two regimes. For  $0 < \varepsilon < 1$  the leading contribution in (27) is of order  $z^{\varepsilon}$ , while for  $\varepsilon \geq 1$  the leading contribution is linear in z. The former regime applies for  $2 > \tau > \frac{3}{2}$  while the latter holds for  $1 < \tau < \frac{3}{2}$ . This gives for the critical exponent at the error threshold

$$\beta^{+} = \max(1, \frac{\tau - 1}{2 - \tau}) \quad . \tag{28}$$

The location of the error threshold is determined by the first term on the RHS of the Eq. 27

$$\alpha_c = \mu \tau \frac{2 - \tau}{\tau - 1} \tag{29}$$

We can see that the error threshold vanishes in the limit  $\tau \to 2$  and diverges for  $\tau \to 1$  which justifies the choice of  $\tau$  within the interval (1,2). We investigated also the case  $\tau = 1$ , where we send  $\mu \to 0$  simultaneously with  $N \to \infty$  with  $\tilde{\mu} = \mu \ln N$  kept fixed. In this case we also observe the error threshold for certain value of  $\tilde{\mu}$ , with exponent  $\beta^+ = 1$ .

#### 5 Evolution on Bethe lattice

Another approach which takes into account the complicated structure of real fitness landscapes uses the so-called holey landscape. This concept reflects the fact that most of the random point mutations which may occur are lethal and the evolution ends in a dead end there. So, we may start with the hypercubic lattice  $\{0,1\}^d$  as in section 3 but leave only viable sites, while all lethal genomes are deleted. The remaining lattice has highly random geometry and the symmetry properties of the hypercube, which enabled us to use the Fourier transform, are no more applicable here. Thus, another scheme of the solution should be looked for.

In fact, topologically disordered lattices are widely studied in solid-state theory. The Bethe lattice is a well-known model of random lattices. It has got that large advantage that many problems can be solved analytically. It is widely used in statistical physics, see [45].

We take the infinite Bethe lattice with the connectivity k. In each site there is a population of individuals. With the uniform probability rate  $\mu$  an individual may jump (mutate) to one of k nearest neighbours' site. Again one site with a selective advantage  $\alpha$  is present and we will study creation of the quasispecies around that site. The unperturbed dynamical matrix  $T^0$  corresponds to the topology of the Bethe lattice. The off-diagonal terms will be  $T^0_{ij} = \mu$  if j and i are neighbours on the lattice and  $T^0_{ij} = 0$  elsewhere. The diagonal terms on a lattice with connectivity k are obviously  $T^0_{ii} = -k \, \mu$  for all i.

Following the general scheme of Sec. 2 we calculate the diagonal element of the resolvent  $\mathcal{G}^0 = (\zeta - T^0)^{-1}$  at the selected site. As in the infinite Bethe lattice all sites are equivalent, we can calculate the diagonal element at any site inside the Bethe lattice. This will be done using the partitioning (projector) method.

The procedure is based in splitting the Bethe lattice into separate parts. This

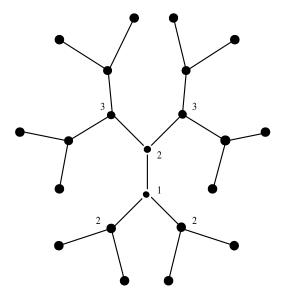


Fig. 3. The Bethe lattice with the connectivity k = 3 and the separation of branches done during the partitioning. The first partitioning takes part in the site 1, the second one in one of the sites 2.

will be done in two steps, as illustrated in Fig. 3. We calculate the diagonal element  $G(\zeta) = \mathcal{G}_{11}^0(\zeta)$  at site 1. First, we separate the central site 1 from the rest of the lattice. Because there are no loops, the rest of the Bethe lattice now consists of k disconnected and identical infinite branches. The branches start at terminal sites denoted by 2.

Let P be the projector to the site 1 and Q = 1 - P the complementary projector, which separates the rest of the lattice. Then, we get for the diagonal element of the resolvent

$$G(\zeta) = P\mathcal{G}(\zeta)P = \frac{P}{\zeta - PT^0P - \Sigma(\zeta)} \quad , \tag{30}$$

where the self-energy has the form

$$\Sigma(\zeta) = PT^0 Q \frac{Q}{\zeta - T^0} Q T^0 P \quad . \tag{31}$$

By extracting the site 1 the lattice consists of k identical parts. So,  $\Sigma(\zeta)$  is a sum of k identical contribution, each of them coming from one isolated branch. We can write

$$\Sigma(\zeta) = \mu^2 k \Gamma(\zeta) \quad , \tag{32}$$

where  $\Gamma(\zeta)$  is the matrix element of the projected resolvent  $(\zeta - QT^0Q)^{-1}$  at any of the terminal sites denoted by 2 in Fig. 3.

The next step of the partitioning takes one branch and separates the terminal

point 2 from it. As a result, k-1 disconnected branches arise. Their terminal points are denoted as 3 in Fig. 3. An equation analogous to (30) is found also for  $\Gamma(\zeta)$ .

We may iterate the same procedure arbitrary number of times. But if we consider infinite Bethe lattice, the branch starting with site 2 must be identical to any of the branches starting at site 3. This leads to closure in the relation for the quantity  $\Gamma(\zeta)$ .

$$\Gamma(\zeta) = \frac{1}{\zeta + \mu k - \mu^2 (k - 1) \Gamma(\zeta)} \quad . \tag{33}$$

Solving the equations (33) and (30) we find the function  $G(\zeta)$ . From the two roots of the quadratic equation the proper one is chosen by the requirement that the resolvent must have correct asymptotic behaviour  $G(\zeta) \sim 1/\zeta$  for  $|\zeta| \to \infty$ .

However, one complication arises here. If we calculate the density of states  $\mathcal{D}(\zeta) = \frac{1}{\pi} \lim_{\varepsilon \to 0} \operatorname{Im} G(\zeta - \mathrm{i}\varepsilon)$ , we observe for k > 2 a gap arising between the upper edge of the density of states and the point  $\zeta = 0$ . This reflects the well-known pathology of the Bethe lattice, which stems from the fact that the surface points of the Bethe lattice constitute finite fraction of the whole even in the thermodynamic limit, unlike lattices embedded in d-dimensional Euclidean space, where the fraction of the surface vanishes as  $N^{-1/d}$  when the number of sites N goes to infinity. When investigating the diffusion on the Bethe lattice, it has the unnatural consequence that the probability density flows out constantly toward the surface and tends to zero in any finite portion of the lattice. In order to compensate for this unnatural effect, we put uniform probability flux into the lattice. In the context of biological evolution, this amounts simply to addition of a constant to the fitness of all genomes. Such an uniform change dos not affect the natural selection and evolutionary competition, but simplifies the mathematical treatment.

Indeed, introducing the uniform probability influx amounts simply to shifting the variable  $\zeta \to \zeta + \mu k - 2\mu\sqrt{k-1}$  so that the upper edge of the density of states is located at  $\zeta = 0$ . The shifted resolvent is then

$$G(\zeta) = \frac{2(k-1)}{(k-2)(\zeta + 2\mu\sqrt{k-1}) + k\sqrt{\zeta^2 + 4\mu\zeta\sqrt{k-1}}} \quad . \tag{34}$$

The real and imaginary part of the shifted resolvent are shown in Fig. 4.

Now we can turn to the solution of (4) using the expression (34). Since we are

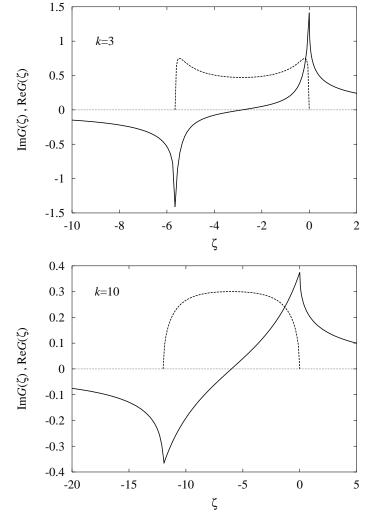


Fig. 4. Real (full line) and imaginary (dashed line) part of the shifted resolvents for k = 3 and k = 10.

looking for the real eigenvalue  $z \ge 0$  we obtain

$$z = \frac{1}{2} \left[ (2 - k)\alpha - 4\sqrt{k - 1}\mu + k\sqrt{\alpha^2 + 4\mu^2} \right].$$
 (35)

This solution is valid only above the error threshold:  $\alpha \geq \alpha_c = \mu(k-2)/\sqrt{k-1}$ . For smaller  $\alpha$  the equation (4) have no real solution, there is no localised state and the largest eigenvalue of the dynamic matrix is z=0.

So we have again found that there is for k > 2 the error threshold between the random wandering regime and the adaptive regime at some positive value  $\alpha = \alpha_c$ . For k = 2 the error threshold disappears,  $\alpha_c = 0$ . However, this case is of little interest for us now, because the Bethe lattice reduces to a linear chain, hardly being a good approximation for the holey fitness landscape we started with.

Close to the the critical point, we obtain that for k > 2 the largest eigenvalue z behaves as a second power of the distance from the error threshold

$$z \simeq \frac{\sqrt{k-1}}{4\mu} (\alpha - \alpha_c)^2$$
, when  $\alpha \to \alpha_c^+$ . (36)

So we have got the critical exponent  $\beta_b^+=2$ . This reflects the behaviour of the density of states at the band edge, which is  $\mathcal{D}(\zeta) \sim |\zeta|^{1/2}$  for any k>2. In fact, we obtained the relation between the exponent  $\beta^+$  and the behaviour of the density of states at the band edge already in Sec. 4 when we investigated the evolution in ultrametric space.

# 6 Super-Universality of the Critical Exponent $\gamma^+$

In all previous cases the critical exponent  $\beta^+ > 0$  has been found. In this section we show that if we consider power behaviour of the largest eigenvalue z near the critical point  $\alpha_c$ , we can find the value of the critical exponent  $\gamma^+$ .

Assume that the whole sequence space contains N distinct points. Then, there are exactly N eigenvalues of the matrix T. It is known that the largest eigenvalue 0 of the unperturbed dynamic matrix  $T^0$  is non-degenerate. If N is very large, we can approximately write for the matrix element of the resolvent  $G(\zeta) \simeq \overline{G}(\zeta)$  corresponding to the diffusion on the lattice with N sites that

$$\overline{G}(\zeta) = \frac{N-1}{N}G(\zeta) + \frac{1}{N}\frac{1}{\zeta} \quad . \tag{37}$$

We want to know what is the dependence of the split-off pole z on the genome size N. It is described by the susceptibility defined in (10).

The Koster-Slater condition written as

$$\overline{G}(z) = \frac{1}{\alpha},\tag{38}$$

which corresponds to (4), can be regarded as an implicit function z(N), so we use the formula for the derivative of the implicit function in order to get the susceptibility  $\chi$  defined in (10). In the thermodynamic limit  $N \to \infty$  the expression simplifies and we find that the susceptibility of the quasispecies to the change of the sequence length is

$$\chi = -\frac{G(z) - \frac{1}{z}}{\frac{\partial G}{\partial z}} \quad . \tag{39}$$

As a next step, in order to find  $\gamma^+$ , we suppose that in the vicinity of the error threshold the highest eigenvalue can be replaced by the term  $z \simeq q(\alpha - \alpha_c)^{\beta^+}$ , where q is an appropriate coefficient. So, close to the error threshold

$$G(z) \simeq \frac{1}{\alpha_c} - \frac{1}{\alpha_c^2} \left(\frac{z}{q}\right)^{1/\beta^+}$$
 (40)

hence

$$\chi = -\frac{\beta \alpha_c^2}{\alpha - \alpha_c}, \quad \text{for} \quad \alpha \to \alpha_c$$
 (41)

which corresponds exactly to (11). The value of the critical exponent  $\gamma^+ = -1$  follows, and we see that the exponent does not depend on the model in question. This proves the super-universality of the exponent  $\gamma^+$ .

#### 7 Conclusions

We investigated the transition between adaptive and neutral phase in biological evolution, which occurs at the error—threshold value of the mutation rate. We suggested to take into account the complicated structure of the fitness landscape by effectively choosing non-trivial topology of the genome space. In all cases we observed the formation of a quasispecies around a site with selective advantage.

We compared the evolutionary process in three different topologies. The first one was the hypercube. (We re-derived by a different method the already known results and completed the study by calculating the susceptibility, not studied before.) This corresponds to standard sharply—peaked landscape, with completely flat landscape as a background. Second, inspired by the theory of spin glasses, we modelled the ruggedness of the fitness landscape by taking as the basic space the set of peaks hierarchically organized in an ultrametric space. Third, we took the holey fitness landscape, in which all viable genomes have equal fitness and all lethal genomes are cut off. We approximated it by the Bethe lattice, as usual in various problems dealing with randomly connected networks in high dimensions.

The problem was treated as diffusion in the underlying space, the site with selective advantage acting as a source. The formation of a localized state (quasispecies) around the selected site was studied by observing the behavior of the maximum eigenvalue of the dynamical matrix governing the diffusion. If the maximum eigenvalue is split off from the rest of eigenvalues (the band), the state is localized and we are in the adaptive phase.

The split-off sets on at the critical value of the selective advantage, corresponding to the error threshold. We calculated the value of the critical value in all three topologies. We therefore confirmed that the very existence of the error threshold phenomenon does not depend on what is the structure of the genome space, at least what concerns the types of topology studied here.

As a measure of the critical behavior we chose the approach of the maximum eigenvalue to zero when the selective advantage approaches its critical value. We found the behavior be dominated by a power and calculated the critical exponent. We found that it is always larger or equal to 1. For the hypercube it is 1, for the Bethe lattice it has value 2, while in the ultrametric space it may assume any value larger or equal to 1, depending on details of the geometry.

In order to find the dependence between the largest eigenvalue and the volume of the genome space, we calculated the susceptibility of the quasispecies to the change of the sequence length. The susceptibility diverge in the vicinity of the error threshold. This could be of the partial interest for biologists, since natural viral population seems to have mutation rate very close to the critical point, see [46]. We found that the divergence of the susceptibility at the error threshold is governed by a power-law with super-universal, model-independent exponent -1.

All the topologies which we considered were regular. Our further outlook is to study the influence of the randomness in the topology of the genome space to the evolutionary process.

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# **Appendix**

We will present the basic facts on ultrametric spaces, p-adic numbers and p-adic Fourier transform here [32,39,41,42].

The ultrametric space is a special kind of a metric space. It is a set  $\mathcal{U}$  of points endowed by a non-negative function expressing the distance between

two points in the space. For reasons which will become clear later, in this article we will use the notation  $|a-b|_p$  for the distance between points  $a, b \in \mathcal{U}$ .

As usual in metric spaces, we require that the distance from a point to itself is zero and distance to any other point is positive. The most important property of ultrametric spaces is that instead of the triangle inequality a stronger condition holds,

$$|a-b|_p \le \max\{|a-c|_p, |c-b|_p\} \quad \forall a, b, c \in \mathcal{U}. \tag{42}$$

This implies that any triangle is equilateral or isosceles with a small base, that every point inside a ball is its centre, or that the diameter equals to the radius. More detailed presentation can be found in [32].

There is a class of the ultrametric spaces formed by p-adic numbers. These are defined as sums

$$a = \sum_{i=0}^{K-1} a_i p^i, (43)$$

where p and  $a_i$ ,  $0 \le a_i \le p-1$ , are natural integers. Clearly  $a \in \{0, 1, ..., p^K - 1\}$ . The distance  $|\cdot|_p$  is defined as  $|a-b|_p = p^{-j}$  where  $p^{+j}$  is the largest divisor of the number |a-b| in that form (j is an integer). Note that  $|a|_p$  can be considered as an (ultrametric) norm of the number a.

The integral over all p-adic numbers is defined as [39]

$$\int_{p} T(a) da = \frac{1}{p^{K}} \sum_{a=0}^{p^{K-1}} T(a), \tag{44}$$

where the sum goes over whole set of p-adic numbers. With so defined integral we have the Fourier transform of the function T(a) in the form:

$$\hat{T}(m) = \frac{1}{p^K} \sum_{a=0}^{p^K - 1} e^{2\pi i ma} T(a).$$
(45)

m is an element of the reciprocal space and it is in the form  $m = \sum_{i=1}^{K} m_i p^{i-K}$ ,  $0 \le m_i \le p-1$ . If the function T(a) depends only on the ultrametric norm, i. e.  $T(a) = f(|a|_p)$ , and if  $|m|_p = p^k$ , we get (for k = 1, ..., K):

$$\hat{T}_{k} \equiv \hat{T}(m) = \tilde{T} + \sum_{l=k}^{K-1} T_{l} p^{K-l-1} (p-1) - T_{k-1} p^{K-k}$$

$$\hat{T}_{0} \equiv \hat{T}(0) = \tilde{T} + \sum_{l=0}^{K-1} T_{l} p^{K-l-1} (p-1) .$$
(46)

In the previous formula we defined,  $\tilde{T} = T(0)$ , and  $T_l = T(a)$  when  $|a|_p = p^{-l}$ . On the other side for  $|a|_p = p^{-l}$  we get the inversion of the Fourier transform in the form (for  $l = 0, \ldots, K - 1$ ):

$$T_{l} \equiv T(a) = p^{-K} \hat{T}_{0} + \sum_{m=1}^{l} \hat{T}_{m} p^{m-K-1} (p-1) - \hat{T}_{l+1} p^{l-K}$$

$$\tilde{T} \equiv T(0) = p^{-K} \hat{T}_{0} + \sum_{m=1}^{K} \hat{T}_{m} p^{m-K-1} (p-1) .$$

$$(47)$$

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